IJCTA, 8(4), 2015, pp. 1573-1585

Hand Feature Descriptor Extraction Techniques for Improving the Gesture Identification System

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Abstract: Gestures are nothing but the motion of the human body that can be used to convey particular information to the listener. They are used as a means of communication among humans and can also be used to create a system for improving the nonverbal communication between humans and computers. The proposed system develops the effective hand gesture identification system using the feature descriptor extraction techniques. The captured images are preprocessed and the hand edges have been segmented by using the segmentation techniques. From the segmented image the contour has been extracted by Multi Resolution based Haar Wavelet Descriptor (MHRWD) and the statistical features have been extracted. The extracted features are classified using the Radial Basis Neural Networks and the extracted features are compared with theFourier descriptors, Determinant of Hessian, SIFT, FAST descriptors. Thus the proposed system extracts the important features from the hand images which are used to improve the gesture identification accuracy.

Keywords: Hand Gestures, Feature Extraction, Multi Resolution based Haar Wavelet Descriptor, Fourier descriptors, moment descriptors.

1. INTRODUCTION

Human Computer Interaction is majorly carried out with the help of additional devices like a mouse or a keyboard. Though this is the most popular method even now, interaction with the computer has revolutionized to become more natural. Humans usually express their emotions by the use of facial expressions, gestures and vocals. Thus, the interaction with the computer can be made more natural if we could use natural gestures for communication. A Gesture based non-verbal communication system does not convey the exact information such as proxemics or expressive displays but it only expresses a person's feelings and thoughts by using the body motion [1]. Gestures include the face, hand, eye expressions and other body parts which are used to establish the communication between the human beings [2]. In the recent years hand gestures are used in various applications like interactive human and machine interface, virtual environment, military, medical applications [3]. These Hand Gestures are captured by several input devices, namely wired gloves, depth-aware cameras, stereo cameras, controller-based gestures, single camera and radar [4].

The captured hand images are processed and classified by passing through various stages such as image segmentation, feature extraction and gesture classification [5]. The performance of the hand gesture recognition system depends on these stages and it is important to develop a system which takes into consideration the accuracy of recognition along with reduced computation time. In the recent research several feature extraction techniques such as Gray Level Co-occurrence Matrix [6], Fourier descriptors [7], moment descriptors [8] are used which extract the useful information. But these feature extraction methods have issues like low level, inaccurate or unwanted feature extraction which causes reduction in the overall performance of the system, increase in the computation cost, reduction in the accuracy of detection and so on [9].

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In this paper an effective hand gesture feature extraction technique has been proposed for extracting the useful and high level information from the hand gestures. Initially the hand gesture image is captured and the captured images are preprocessed and subtract the background by applying the segmentation techniques. Then the Multi Resolution based Haar Wavelet Descriptor (MHRWD) technique is applied for extracting the meaningful contour and related features are extracted from the resultant contour image and extracted features are compared with the Fourier descriptors, Determinant of Hessian, SIFT, FAST descriptors. The extracted features are classified by applying the Radial Basis Function Neural Networks and the performance of the proposed system is evaluated with the number of features, Execution time and so on. Thus the proposed system extracts the most important and efficient features that are used to improve the gesture recognition accuracy.

2. RELATED WORKS

Hand Gestures are playing an important role in the recsent research. This section deals with the various discussions about the hand gesture recognition process. Renqiang Xie et al., [10] discuss about the accelerometer smart ring and similarity matching based hand gesture recognition process. In this paper simple and complex hand gestures are analyzed by wearing the ring in the hand. The ring capture the hand motions in different accelerometer and the features are extracted from those captured motions. The simple gesture features are encoded using the Johnson code which is stored as a template in the database. Then the complex gestures match with the template by applying the similarity matching process to recognize the gesture with greatest accuracy. The performance of the proposed system is evaluated by creating 8 basic gestures and 12 complex gestures.

Xingyu Wu et al., [11] proposed a new hand gesture recognition approach to overcome the shortcoming of the view invariance based hand gesture recognition process. The author extracts the shape descriptors from the 3D trajectory based hand gesture image. The extracted shape descriptors are used to identify the viewpoint of the changes, different angle of the rotation in the hand gesture. Then the performance of the proposed system is evaluated with the help of the Australian Sign Language database and the Kinect Hand Trajectory database which gives the higher average recognition rate when comparing to other approaches.

Chenglong Yu et al., [12]developing the multi-layer perceptron based neural network for recognizing the hand gesture. The captured image is preprocessed by applying the median and smoothing filter. Then the hand color related features, Hu-invariant features, Fourier descriptor, region are extracted based on the contrast of the image. The extracted features are recognized by using the MLP network and the performance of the proposed system is evaluated using the 3500 hand gesture image which gives the highest recognition rate.

Aowal et al., [13] presents that the two dimensional Zernike moments based hand gesture recognition system. The author extracts the these moment features from captured image which is considered as the fixed order moment that is used to classify the intra class variance feature. These features estimate the discrimination power of each moments present in the hand gesture. Then the features are classified by applying the nearest neighbor classifier and the performance of the system is evaluated with the help of the existing methods such as conventional principal component analysis, ZM based methods, Fourier descriptor.

Collumeau et al., [14] proposed a new approach for managing the hospital surgeons equipment by applying the novel hand gesture recognition process. This process uses the 9750 hand gesture images to make the performance analysis process. From the captured hand image the geometric descriptors are extracted which is used to measure the contour convex of the hand. Then the extracted features are compared with the Hu moment in variant, SIFT and HOG features. Then the extracted features are provided higher recognition rate than compared to the other rotation features.

Dardas et al., [15] developing the bag of words based hand gesture recognition process. Initially the key points have been extracted from the hand image, then the scale invariance feature transform is applied to the image for extracting the invariant feature. Then the vector quantization rule is applied to the image for unifying the process. Finally the features are clustered by using the k-means clustering process and the multi-class classification is performed by applying the support vector machine approach. This multi class classifier classifies the feature with accurate manner. Thus the proposed system uses Multi Resolution based Haar Wavelet Descriptor for recognizing the Hand Gestures which are explained in the following sections.

3. PROPOSED SYSTEM

In this propose system Cambridge Hand Gesture Data set is used for recognizing the Gestures. The recognition process consists of different phases, namely image processing, Background subtraction, Edge Detection, Feature Extraction and the recognition process. Then the proposed system block diagram is shown in the figure 1 which explains how the proposed system recognize the hand gestures with higher recognition rate.

The edge detected hand images are fed into a feature extraction process for extracting the meaningful descriptors. Then the optimal descriptors like contour based feature, mean, variance, standard deviation are extracted by using the Multi Resolution based Haar Wavelet Descriptor (MRHWD) and the classification is performed by applying the Radial Basis Function Neural Networks (RBFNN).

Initially the impulse noise has been removed by using the Non-Local Mean filter [16] which is calculating the

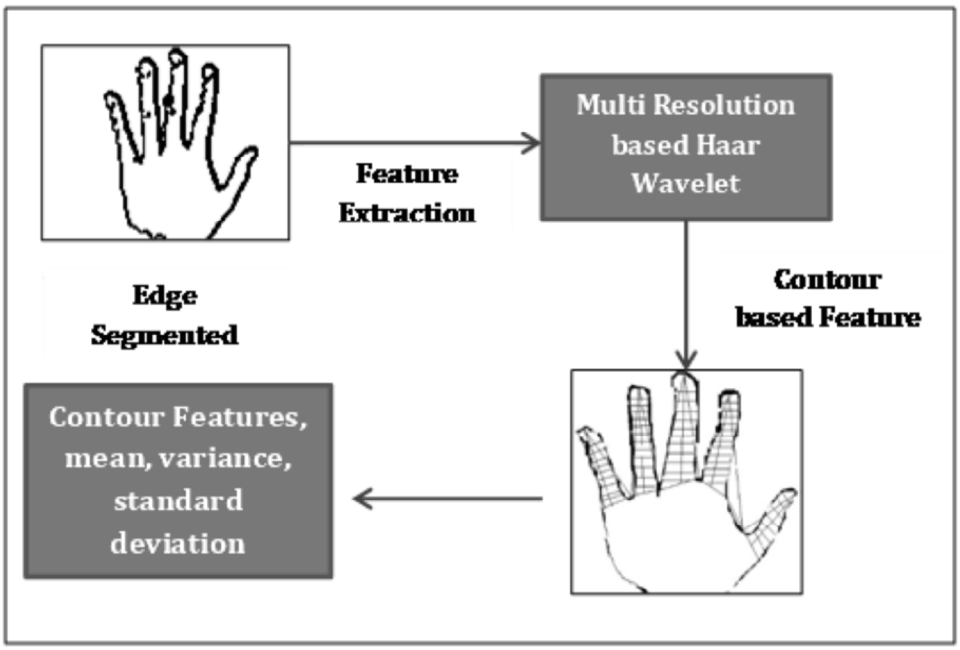


Figure 1: Proposed Multi Resolution Haar Wavelet based System

weighted value of each pixel present in the image and comparing with the target pixel value. The weighted value is estimated as follows,

$$u(p) = \frac{1}{c(p)} \int v(q) f(p,q) dq \tag{1}$$

Where, $C(p)$ is the normalized factor

$u(p)$ represents the filtered value of the image

$v(q)$ is the unfiltered value of the image

$f(p, q)$ is the weighted function

If the pixel is corrupted by any noise, it has to be changed according to the weighted value. Then the image background has to be initialized by applying the selective averaging method which is defined as follows,

$$BM_N(x,y) = \frac{\sum_{m=1}^{N} I_m(x,y)}{N} \tag{2}$$

After initialize the background pixel value, Gaussian density function has been calculated for estimating the pixel probability value. Then the Gaussian density function is calculated as follows,

$$p(x \mid \lambda) = \sum_{i=1}^{M} w_i g(X \mid \mu_i, \Sigma_i) \tag{3}$$

Then the weight value is updated continuously for eliminating the unwanted pixels presented in the hand gesture image. Finally the new background pixel value is calculated as follows,

$$B = \arg\min_b \left(\sum_{i=1}^{b} \omega_{i,t} > T \right) \tag{4}$$

Then the Gesture edges have been detected by using the Improved Global Swarm Optimization based Canny edge detection and the Multi Resolution based Haar Wavelet Descriptor (MRHWD) are extracted as follows,

3.1. Hand Gesture Descriptor Extraction Methods

Hand Gesture is playing the crucial role in sign language and the military application. In this paper the hand gesture descriptors are extracted by applying the Multi Resolution based Haar Wavelet Descriptor and which is compared with several existing methods such as Fourier descriptors, Determinant of Hessian, SIFT, FAST descriptors.

3.1.1. SIFT Descriptors

Scale-Invariant Feature Transform (SIFT) [17] is one of the feature descriptor extraction method which is used to derive the local feature from the image. The SIFT descriptor extracts the features based on the relative position because the position of the key features does not change from image to another image. So, the method extracts the descriptors based on the direction, rotation, position of the input image. This method has following stages, namely key point detection, key point location, orientation assignment and keypoint descriptors. In the key point detection, the image is combined to work with the Gaussian filter. So, maximum and minimum value have been calculated from the edge segmented image which is obtained as follows,

$$D(x, y, \sigma) = L(x, y, K_i\sigma) - L(x, y, K_j\sigma) \tag{5}$$

Where $D(x, y, \sigma)$ is the difference of the Gaussian image, $L(x, y, K\sigma)$ is the convolution value of the image, $l(x, y)$ is the Gaussian blur value,

$$L(x, y, K\sigma) = G(x, y, k\sigma) * l(x, y) \tag{6}$$

After detecting the key point, the key point have been located for identifying the exact features of the image. The key point position has to be determined and then the location and scale of the key point has been calculated by applying the Taylor series which is obtained as follows,

$$D(x) = D + \frac{\partial D^T}{\partial_x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \tag{7}$$

Then the orientation has been assigned as follows, which is used to identify the direction of the particular key point, measured by the magnitude and orientation estimation.

$$m(x,y)=\sqrt{\left(L(x+1,y)-L(x-1,y)\right)^2+\left(L(x,y+1)-L(x,y-1)\right)^2} \tag{8}$$

$$\theta(x,y)=\mathrm{a\ tan\ 2}\left(L(x,y+1)-L(x,y-1)\right),\left(L(x+1,y)-L(x-1,y)\right) \tag{9}$$

Where, $m(x, y)$ = *magnitude of the key image*,

$\theta(x, y)$ = *orientation the key point image*

Finally the key point descriptors are extracted by analyzing the key point detector and the orientation assignment process. In which the image has been divided into the 4×4 histogram orientation and each orientation has the 16×16 region of the key points which has 8 bins and 28 elements. Those elements are normalized by using the threshold value 0.2. The key point which lies within the threshold value is considered as the hand feature. The SIFT descriptor based hand feature extract is shown in the following figure 2.

Then the extracted feature is stored as a template in the database for further hand gesture recognition process.

Figure 2: SIFT Hand Features

3.1.2. Fourier Descriptors

Fourier Descriptor [18] is one of the shape relevant descriptive approach that is used to retrieve the image content from the segmented image. In the Fourier Descriptor, two important features are extracted, namely complex coordinates and centroid distance. These two measures are used to identify the shape descriptors with accurate manner. The complex coordinate is the complex number generation approach from the image boundary coordinates which is calculated as follows,

$$z(t)=x(t)+iy(t) \tag{10}$$

Then the shifted coordinates have been applied to the complex function as follows for eliminating the effect of the bias.

$$z(t)=[x(t)-x_c]+i[y(t)-y_c] \tag{11}$$

Where (x_c, y_c) is the centroid of the shape that is called as the average of the boundary coordinates. Then the centroid of the shape is estimated as follows,

$$x_c=\frac{1}{L}\Sigma_{t=0}^{L-1}x(t), \qquad y_c=\frac{1}{L}\Sigma_{t=0}^{L-1}y(t), \tag{12}$$

After calculating the complex coordinates, centroid distance has to be calculated which is used to estimate the distance between the boundary points from the centroid of the shape. Then the centroid distance is calculated as follows,

$$r(t) = ([x(t) - x_c]^2 + [y(t) - y_c]^2)^{1/2} \tag{13}$$

These estimated centroid shape and centroid distance descriptors are used to identify the shape of the hand gestures from the segmented image because the extracted features are invariant to translation which is shown in the figure 3.

Figure 3: Fourier Descriptors

3.1.3. Hessian Descriptors

Hessian Descriptor [19] is also called as the Determinate of the Hessian Descriptor (DoH) which is mostly used in the SURF feature extraction process. This process extracts the multi-scale object and determine the Hessian matrix at the maximum value. The Hessian matrix is calculated by using the second order derivative method. It has two steps such as interesting point detection and description of the interesting point. Initially the interesting point is calculated by using the hessian matrix because it reduces the computation time during the feature extraction process. Then the interesting point is calculated as follows,

$$I_x = \sum_{i=0}^{i \le x} \sum_{j=0}^{i \le y} I(i, j) \tag{14}$$

Where I_x is the integral image. From the image the Hessian matrix is formed as follows,

$$H(x:\sigma) = \begin{bmatrix} L_{xx}(x;\sigma) L_{yx}(x;\sigma) \\ L_{xy}(x;\sigma) L_{yy}(x;\sigma) \end{bmatrix} \tag{15}$$

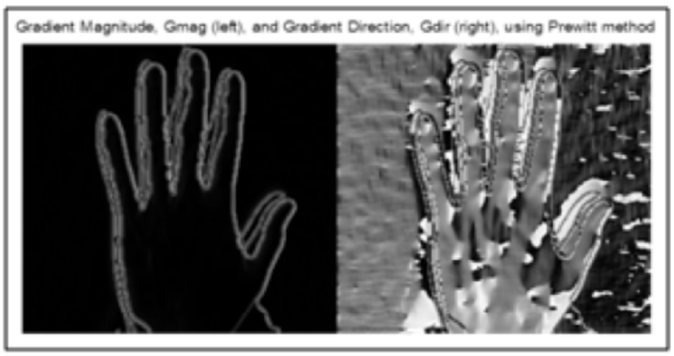


Figure 4: Hessian Based Hand Features

Where L_{xx} $(x; \sigma)$ is the convolution of the Gaussian second derivative of the image I. After extracting the interesting point, then the neighborhood value and location is calculated by applying the Haar wavelet in circular direction. The direction based extracts features shown in the figure 4.

From the different direction the descriptors and the related scale have been estimated which is used in the recognition process.

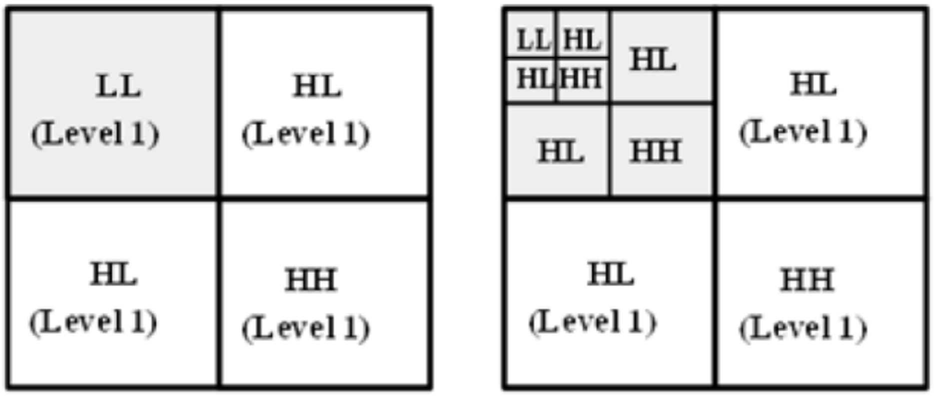
3.1.4. Multi Resolution based Haar Wavelet Descriptor

The proposed system uses the Multi Resolution based Haar Wavelet Descriptor (MRHWD) for extracting features from the edge detected hand gesture image. If the edge segmented images have n^2 pixels, then it has n^2 coefficients which makes the feature extraction process more complicated. So, the Haar wavelet transform is used to decompose the edge segmented images into two components, namely approximation and details which used to extract the optimal features like contour, mean, variance from the hand gesture image. If the edge segmented images has $a = a_1, a_2, \ldots \ldots a_n$ average (approximation) pixel values which have the image length $f = f_1, f_2, \ldots \ldots f_n$ and the detail pixel value like $d = d_1, d_2, \ldots \ldots d_n$. Then approximation and detail coefficient is calculated as follows,

$$a_n = \frac{f_{2n-1} + f_{2n}}{\sqrt{2}} \qquad n = 1, 2, 3, \ldots \ldots n/2 \tag{16}$$

$$d_n = \frac{f_{2n-1} - f_{2n}}{\sqrt{2}} \qquad n = 1, 2, 3, \ldots \ldots n/2 \tag{17}$$

From the above equation the approximation and detail coefficients are calculated which is used to decompose the original edge segmented image into the lower resolution based image. The decomposed image provides the information about the global properties of the analyzed image, vertical lines of the hidden image, horizontal lines from the hidden image and the diagonal area information from the hidden image. These informations are used to extract the features with minimum computation time and high computation speed. Then the sample decomposed image is represented as follows,



a]Edge Segmented Image

b] Decomposed Image

From the decomposed image the contour oriented features are extracted by using the two different steps like patch computation and local descriptors identification process. In the patch computation stage, the patch is selected according to the image pixel value which depends on the image orientation and rotation. Based on the rotation and orientation the different patches are selected and those patches are normalized for estimating the descriptors. The normalized patches are used to ensure that the calculated patches having the 0 mean value and 1 standard deviation which ensure that the extracted descriptors are never changed. In the next stage local descriptors are estimated for each band in the decomposed image by applying the Haar Wavelet function which minimize the number of features.

Normally the Haar wavelet function is denoted as follows,

$$\varphi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2} \\ -1 & \frac{1}{2} \le t < 1 \\ 0 & otherwise \end{cases} \tag{18}$$

The above wavelet function has the unit interval value [0,1].

The decomposed image is shown in the figure 5.

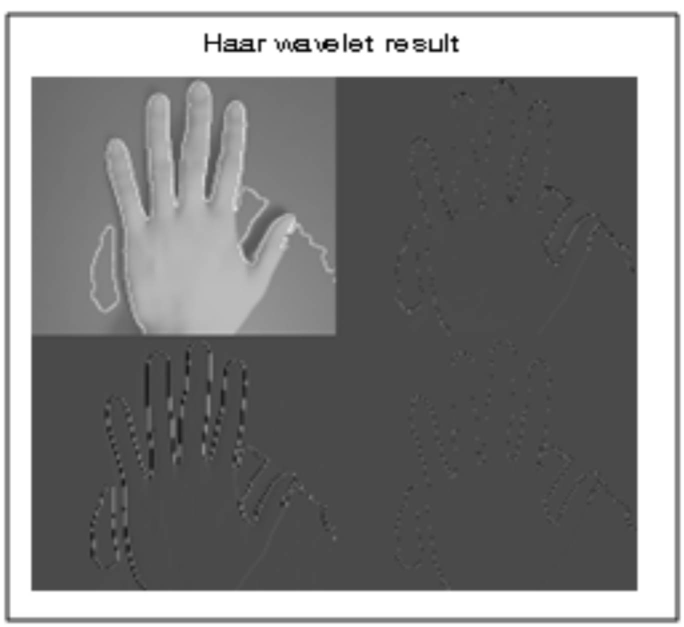


Figure 5: Haar Wavelet Transform

From decomposed image, mean, variance and standard deviation, entropy features are extracted as follows,

Table 1
List of Features

Features	*Related Formula*
Entropy	$\sum_{i,j=0}^{n-1} -\ln(P_{ij})P_{ij}$
Variance	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}(i-\mu)^2.p(i,j)$
Mean	$\sum_{i=0}^{2(n-1)} i.p_{x+y}(i)$
Standard Deviation	$\sqrt{\left(\sum_{i=0}^{2(n-1)} i.p_{x+y}(i)\right)^2}$

The extracted low-high and high-low descriptors depends on the edge position. Thus the proposed descriptor method extracts all the detailed features like, low-low, low-high, high-low and high-high features are extracted in the efficient manner. These extracted features entropy, mean, standard deviation, variance is produced the exact information about the particular hand gesture. Then the features are fed into the Radial Basis Neural Network classifier which train the features based on the radbas activation function. The radbas is the neural networks train function which is used to calculate the layers output from its net input value. The neural network has two important parameters, namely centers and spread. Initially the cluster or number of gesture class has been identified and centroid of the each cluster is estimated by using the K-means clustering process which is defined as follows,

$$argmin \sum_{i=1}^{k} \sum_{x\in s_i} \left\|x-\mu_i\right\|^2 \tag{19}$$

Where μ_i is the mean at the center point s_i. Based on the centers the incoming features are trained according to the radbas activation function. Then the distance between the centroids are estimated using the Hausdroff distance [35] measure which is calculated as follows,

$$d_H(X, Y) = \max\{\sup_{xeX} \inf_{yeY} d(x, y), \sup_{yeY} \inf_{xeX} d(x, y) \tag{20}$$

From the estimated distance the hand gestures are trained and classified by using as follows

$$y_k(x^p) = \sum_{j=0}^{M} W_{kj}\phi_j(x^p) \tag{21}$$

Based on the training the testing features are matched with the template by applying the Haudroff distance which is calculated as follows,

Where, $d_H(X, Y)$ - Distance between the features

Then the proposed system extracts the optimal and high level descriptors from the dynamic hand gestures and recognizes those features by using the limited network structure. Thus the performance of the proposed system is evaluated with the help of the experimental results and discussion which is explained in the following section.

4. RESULTS AND DISCUSSION

4.1. Experimental Dataset

In this proposed system Cambridge Hand Gesture Data set [22] is used to recognize the gestures by applying the several image processing techniques. The captured image are preprocessed by applying the Non-Local Mean Filter and the background has been eliminated using the Fuzzy based background subtraction method. Then the fine edged are segmented by applying the Improved IGSOCED and the optimal features are extracted from the edge segmented image. Then the extracted image features are compared with the several existing methods such as Fourier descriptors, Determinant of Hessian, SIFT, FAST descriptors. Then the sample images are shown in following figure 6 which was taken from the captured Hand Gesture Data set.

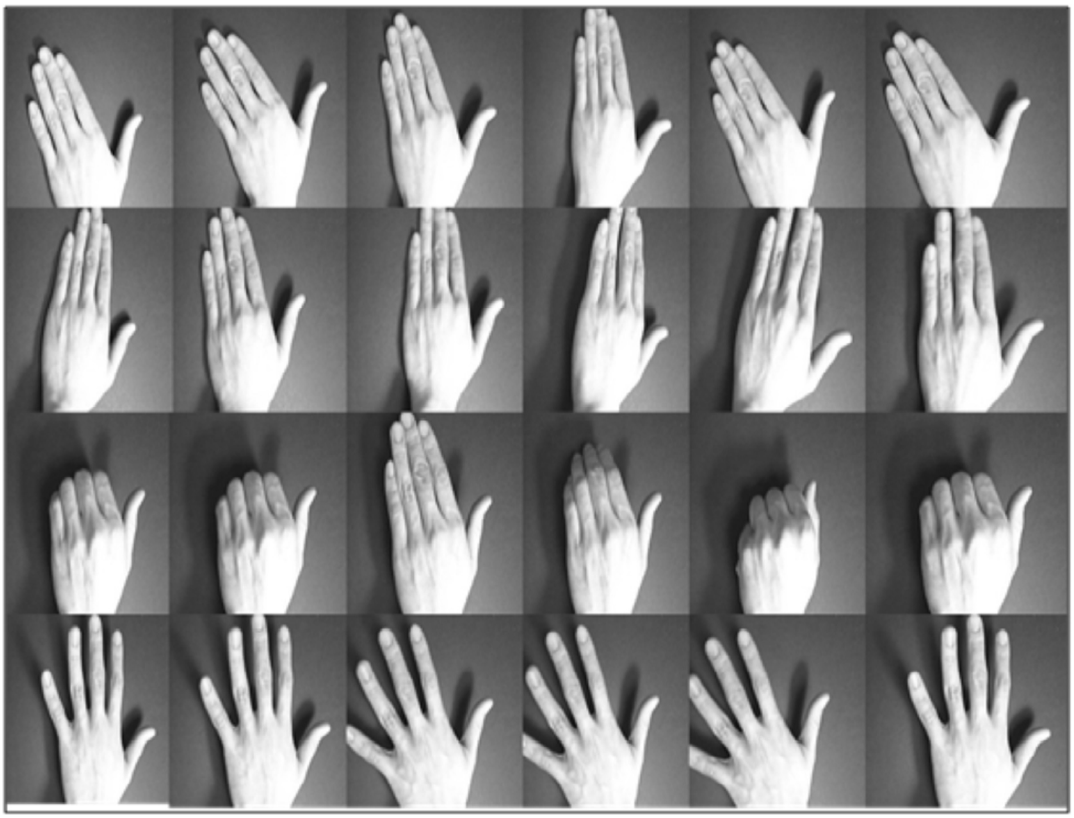


Figure 6: Sample Cambridge Hand Gesture Data set

The Cambridge data set images are captured with different direction, shape, motion and it has 900 images with 9 different sequences of gesture classes. These classes are used to define the 3 primitive hand shapes and motions. In the data set 100 images are used as testing image and those images are analyzed with different direction and shape based descriptors. These images are processed by preprocessing, segmentation process and the features are extracted with the help of the Multiresolution based Haar Wavelet Descriptors (MRHWD). Then the performance of the proposed system is evaluated with the help of the Accuracy of the extracted features, Detectability of the extracted features and Execution time performance metrics.

4.2. Accuracy

Accuracy [23]is the measure which is used to how the proposed system features are recognize the hand gestures while matching the template with the testing features. Then the resultant accuracy is compared with the existing methods such as Fourier descriptors, Determinant of Hessian, SIFT, FAST descriptors which are shown in the table 2. The Accuracy of the feature is calculated as follows,

$$Accuracy\ of\ \ the\ Feature = \frac{Number\ of\ \ feature\ extracted}{Total\ \ Number\ of\ \ feature} * 100 \tag{22}$$

Table 2
Accuracy of Extracted Features

S. No	*Methods*	*Accuracy of Features Extracted (%)*
1	Fourier descriptors	75.36
2	Determinant of Hessian	81.14
3	SIFT	82.47
4	FAST descriptors	86.67
5	Proposed MRHWD	96.64

The proposed system extracts the optimal features with highest accuracy rate and the related graph representation is shown in the figure 7.

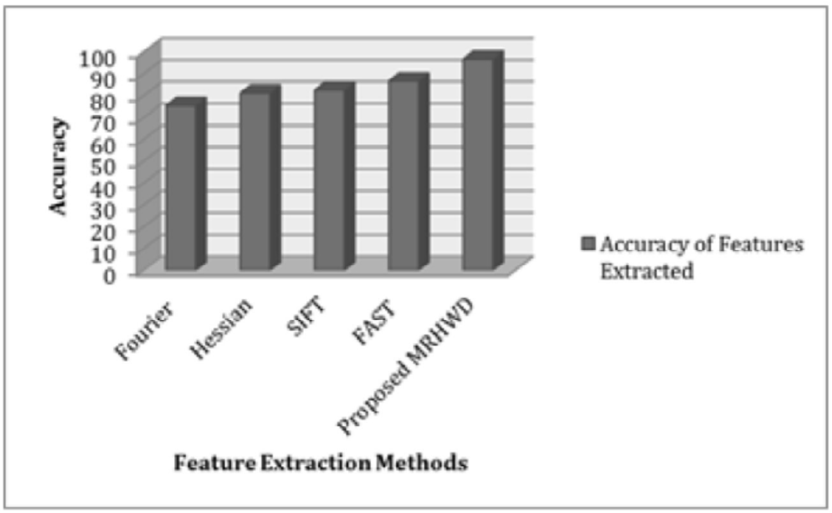


Figure 7: Accuray of Extracted Feature

4.3. Detectability

Detectability [24] is the measure which is used to analyze whether the extracted features are important to making the pattern recognition process. Then the performance of the proposed system detectability value is shown in the following table 3.

Table 3
Detectability of Extracted Features

S. No	*Methods*	*Detectability of Features Extracted (%)*
1	Fourier descriptors	0.5
2	Determinant of Hessian	0.612
3	SIFT	0.687
4	FAST descriptors	0.76
5	Proposed MRHWD	0.993

The above table 3 clearly shows that the proposed features are efficiently used in the recognition process which means, the proposed system eliminates the unwanted features also extract only the meaningful information from the edge segmented image. Then the number of feature extracted execution time is explained as follows,

4.4 Execution Time

Execution time [25] is used to calculate how fast the proposed system extracts the features. During this computation time, keypoint detection and identification time also calculated. The execution time of the proposed system is shown in the table 4.

Table 4
Execution Time of Extracted Features

S. No	*Methods*	*Execution Time of Features Extracted (s)*
1	Fourier descriptors	16.869
2	Determinant of Hessian	16.07
3	SIFT	14.10
4	FAST descriptors	13.514
5	Proposed MRHWD	9.64

The above table 4 clearly shows that the proposed system consumes minimum time for extracting the best features.

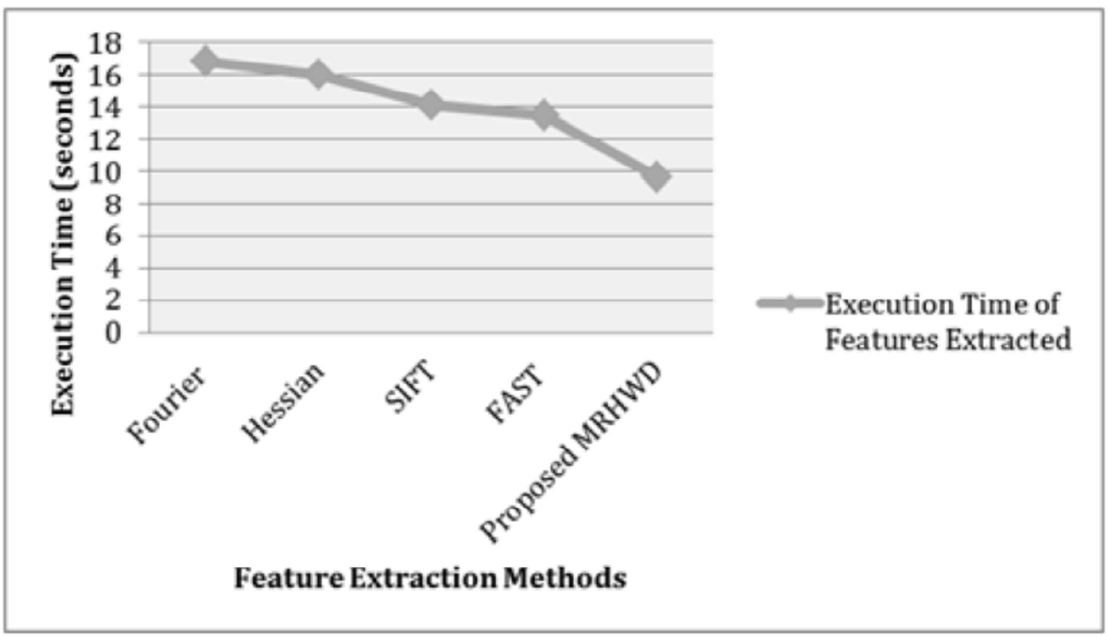


Figure 8: Execution Time of Extracted Feature

The detectability of the features, accuracy of the features are used to recognize the features with high accuracy. The recognition ratio is used to measure the hand gesture identification accuracy which is described as follows,

$$recognition\ ratio = \frac{recognized\ gesture}{tested\ gesture} * 100 \tag{23}$$

Based on the above equation, the recognition rate value is listed in the table 5.

From the above table it clearly shows that the proposed feature extraction method used to improve the hand gesture recognition rate with 97.115 % when compared to the other extraction methods. The related graphical representation is shown in the figure 9.

Table 5
Recognition Ratio

Model	*Data set*		*Recognition Ratio (%)*		
	Training	*Testing*	*Training*	*Testing*	*Overall Rate*
Fourier descriptors	900	100	60.56	52.78	56.67
Determinant of Hessian	900	100	75.98	60.26	68.12
SIFT	900	100	84.08	84.18	84.13
FAST descriptors	900	100	95.23	93.97	94.69
Proposed MRHWD	900	100	99.48	94.75	97.115

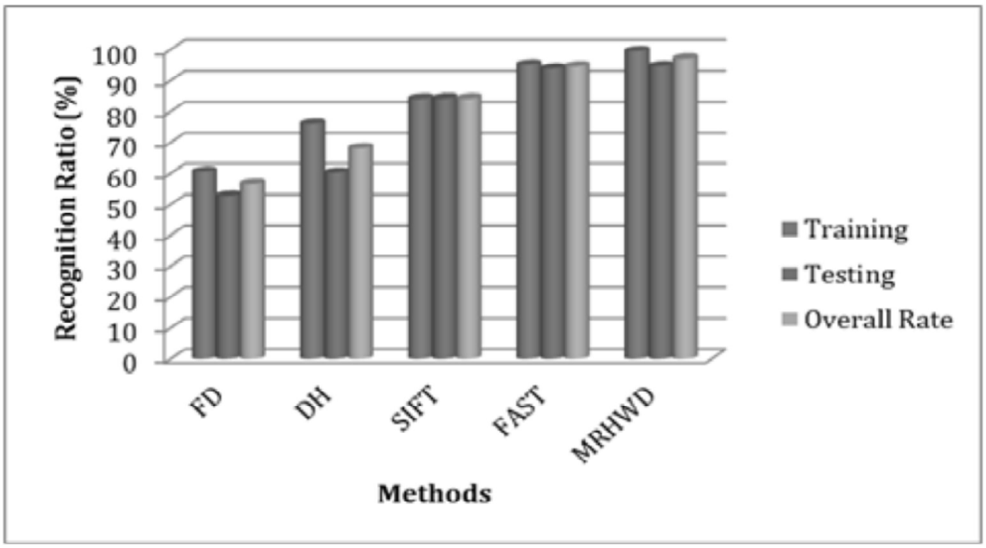


Figure 9: Recognition Rate

These above discussed metrics are used to justify that the proposed Multi Resolution based Haar Wavelet Descriptors (MHRWD) extract the optimal features with highest accuracy rate also it overcomes the other feature extraction problems which is evaluated with the help of the accuracy, detectability and the execution time parameters.

5. CONCLUSION

Thus the paper introduces the Multi Resolution based Haar Wavelet Descriptors (MRHWD) for extracting the hand gesture features. In this paper Cambridge Hand Gesture Data Set is used to recognize the gestures with higher accuracy rate. The captured images are preprocessed and the segmented with the help of the Non-Local Mean Filter and the Gaussian Mixture Model. Then the different level features are like high and low extracted from the edge segmented image. This feature extraction process eliminates the unwanted features and also reduces the execution time while doing the feature extraction. Then the extracted features entropy, mean, variance, standard deviation are fed into the Radial Basis Function Neural Network for recognizing the templates which are stored in the database. Finally the performance of the proposed system is evaluated with the help of the accuracy, detectability and execution time metrics which is compared with the various feature extraction methods such as Fourier descriptors, Determinant of Hessian, SIFT, FAST descriptors. Then proposed system extracts the featurewith 96.64% accuracy and the extracted features are recognize the hand gesture with 97.115% recognition rate in minimum execution time. Thus the proposed system achieves better results which are discussed in the experimental results.

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